Measuring the Effects of Search Costs on Equilibrium Prices and Profits *

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Abstract

This paper assesses the effects of search costs on equilibrium prices and profits. My empirical strategy uses data on purchases of laundry detergent and combines a "front-end" estimation of the demand and cost parameters with a "back-end" analysis to evaluate the effects of search costs. I find that the profits of some firms initially rise and then fall for larger search costs. The magnitude and direction of the effects of search costs on equilibrium prices and profits are heterogeneous, because search costs create incentives that work in opposite directions. My results show that the impact of search costs on prices and profits depends on the relation between actual prices and consumers' prices beliefs.

Keywords: search costs; information; consideration set; pricing; market performance; discrete-choice models

JEL codes: D12; D43; D83; L13; L81

1 Introduction

Empirical evidence suggests that consumers often times have incomplete information about the prices and characteristics of the available alternatives, and thus need to engage in costly search before making their choices (Stigler, 1961; Wildenbeest, 2011; De los Santos, Hortacsu, and Wildenbeest, 2012). These information and search frictions have implications for firms, because they

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affect competitive behavior and firms' incentives (Baye, Morgan, and Scholten, 2007). In particular, from a firm perspective, the cost of searching an additional product creates two incentives that work in opposite directions. On the one hand, search costs[1] create an "investment" incentive for a firm to reduce prices: firms "invest" to push a product into the consumer's consideration set[2], which causes a competitive pressure to lower prices. On the other hand, search costs create a "harvesting" incentive for a firm to raise prices: the number of searched products falls for larger search costs, thus reducing the competition among searched products and allowing a firm to extract rents from consumers with a greater preference for its product. Even without an "investment" incentive, the effect of larger search costs on profits can be either positive or negative, because price competition is lower with higher search costs, but the probability of searching falls for larger search costs.

The direction of the effect of search costs on prices and profits is therefore an empirical question, whose answer may depend on the magnitude of search costs.[3] In this paper I address this question and evaluate the impact of larger search costs on equilibrium prices and profits in a real world setting. I further evaluate the importance of consumers' price beliefs for the effects of search costs on prices and profits.

Identification of the direction and magnitude of the effects of search costs is economically important. Firms can employ strategies and choose actions to influence search costs. Firms therefore want to know the level of search costs for which their profits are the highest, so that they can take the necessary actions to achieve that value. Even if firms cannot choose an exact level of search costs, they may choose actions that yield different search costs and thus knowing the profits in each situation allows them to choose the best alternative. Regulators, competition authorities, and antitrust agencies also benefit from knowing the effects of search costs. If regulators or competition authorities can either take actions to influence search costs or enforce firms to take such actions, then they need to know the effects of search costs on equilibrium prices and profits so that they can choose the best policy.

In order to find the equilibrium prices and respective profits for different levels of search costs, I consider a methodology that combines a "front-end" estimation of the demand and cost parameters with a "back-end" analysis to evaluate the equilibrium prices and profits for different search costs. The general strategy is as follows. First, I estimate demand and search costs. I then use the

[1]Hereafter the expression "search cost" refers to the cost of searching an additional product. I will use the expression "fixed search costs" to refer to search costs that do not depend on the number of searched products. My definition of search costs includes both the costs consumers incur to find out about the characteristics of a product and shopping costs.

[2]I refer to a consideration set as the optimal subset of products searched by a consumer and within which the consumer makes an explicit utility comparison before choosing the product to purchase.

[3]For instance, Moraga-Gonzalez, Sandor, and Wildenbeest (2014) point out that a rise in search costs when their value is small tends to reduce the number of searched products, thereby reducing the elasticity of demand and allowing for higher prices; whereas a rise of search costs when their value is high affects the decision of whether to search, which can yield a fall in prices.

demand and search cost estimates jointly with pricing rules implied by a Nash-Bertrand pricing game to recover marginal costs from the profit maximization first order conditions. Finally, I use the estimates to evaluate numerically the equilibrium prices for different values of search costs and calculate the profits associated with each of these values. I perform the analysis using household panel data on shopping trips and purchases of liquid laundry detergent.

One of the challenges of this analysis is that the effects of search costs on firms incentives depend on how consumers form their price beliefs, but those price beliefs are not observed. Although consumers do not observe actual prices before searching, they may receive some signal about those prices before the search process starts, which affects the formation of their price beliefs. The existence or not of this signal and how it informs about actual prices have implications on firms' incentives. For instance, if there is not a signal and consumers' price beliefs do not depend on actual prices, search costs create only a "harvesting" incentive for firms. In contrast, the "investment" incentive may be stronger than the "harvesting" incentive if there is a signal that provides complete information. I address this issue by evaluating what happens for different assumptions regarding the relation between actual prices and consumers' price beliefs.

I find that the effects of search costs on profits differ across products: for some products the profits are an inverted U-shaped function of search costs, whereas for other products the profits always fall for larger search costs. The inverted U-shaped relation between profits and search costs for some products occurs both when consumers' price beliefs do not depend on actual prices and when consumers have some or full information about actual prices. Yet the number of products for which profits can rise with search costs and the magnitude of this rise are larger when consumers' price beliefs and actual prices are less correlated. Hence, the potential for increasing profits with larger search costs is lower when information frictions are lower.

I show that the "investment" incentive tends to be less important than the "harvesting" incentive, unless information frictions are low. The equilibrium prices of almost all products increase with search costs for low levels of information, even though the magnitude of these increases is heterogeneous. The direction of the effect of marginal search costs on equilibrium prices differs across products and can depend on the level of search costs when the level of information is more precise. My results provide support for theoretical findings that the impact of search costs on prices depends on whether prices are observable (Wolinsky, 1986; Haan and Moraga-Gonzalez, 2011).

I explore the implications of heterogeneous search costs across products by evaluating the effects of the search costs of one product on prices and profits of all products. Larger search costs of a product lower the profits of that product and increase the profits of products that are not searched together with that product, but may reduce the profits of products that are usually searched together. Limited information and costly search can therefore create market power and yield larger profits.

My work is closely related to the literature on search costs. In particular, it relates to work that evaluates and quantifies the effects of search costs on prices and profits. Mehta, Rajiv and Srinivasan (2003) show that the size of the optimal consideration set increases with the price variance and is larger in product categories with greater price variability; and Wildenbeest (2011) finds that increasing the share of consumers with very low search costs results in higher prices with product differentiation and search frictions.

In a paper close to mine, Moraga-Gonzalez, Sandor, and Wildenbeest (2014) evaluate the effects of search costs on prices and profits. They show that search frictions can result in higher, equal, or lower prices, and derive conditions under which higher search costs yield lower prices. In their models higher search costs may result in lower prices by affecting the decision of whether to search at all. Consumers with more elastic demand are the first consumers who stop search and thus higher search costs may increase the relative importance of inelastic consumers for firms, thereby creating incentives for firms lowering prices. Heterogeneity on search costs explains why search costs create two effects on prices that work in opposite directions. In particular, the proposed utility specification implies that the elasticity of each consumer is determined by the level of search costs, which explains why consumers with more elastic demand are the first consumers who stop search. In my model, however, consumers with higher search costs may have a higher valuation of the good and therefore may not be the first consumers who stop search. Hence, the finding of Moraga-Gonzalez, Sandor, and Wildenbeest may not hold in my setting. They and I therefore propose alternative reasons for the potential fall in prices with search costs.[4] Their models further differ from mine by assuming that the quality of the good is unknown before searching and thus ex-ante all firms are equal for consumers. This assumption implies that all firms set the same price in a nonsequential search model and consumers' problem is simply to choose how many products to search. In my model, even before searching, products are heterogeneous and search costs may differ across products. Hence, consumers need to choose which products to search and not only how many products to search.

My results are related and provide support for work that studies the incentives of a firm to raise its own search costs. Ellison and Ellison (2009) show that internet retailers often engage in obfuscation–practices that frustrate consumer search or make it less damaging for firms–which lowers price sensitivity on some other products. Hence, improvements in search technologies need not make search more efficient (Ellison and Wolitzky 2012). Wilson (2010) further finds that in a sequential search model a firm can profitably soften competition by committing to increase its search costs. In equilibrium, firms vary in their provision of information such that costs are asymmetric.

My empirical findings are further related and in line to theoretical work that shows that the

[4] In the framework proposed by Moraga-Gonzalez et al. (2014) the price mechanism affects the intensity with which consumers search–which they call the intensive margin–and the decision of whether to search–denoted by extensive margin. These two margins may be affected in opposing directions.

impact of search costs on prices depends on whether prices are observable. In a seminal paper, Wolinsky (1986) proposes a search model for differentiated products where consumers choose the order of the firms to visit. This model suggests a positive relation between prices and search costs when prices are not observable. Haan and Moraga-Gonzalez (2011) show that the relation between prices and search costs becomes negative when prices are observable. The importance of these findinds is augmented by the empirical evidence that consumers hold simple expectations and behave as if they did not revise their beliefs (Fevrier and Wilner 2013).

My research further relates to work that models and analyzes the importance of imperfect information and search costs on pricing strategies (Varian, 1980; Salop and Stiglitz, 1982; Pancras, 2010). Those papers show that imperfect information and search costs create different levels of consideration that firms can use to price discriminate consumers. De Clippel, Eliaz and Rozen (2014) show that limited attention of consumers may justify the use of prices to deflect or draw attention to a specific market. They propose a model in which consumer inattention decreases the average transaction price in equilibrium because of the competition among firms to stay under the consumers' radar. There are similarities between the "investment" incentive proposed in my paper and the new dimension of competition across firms proposed by De Clippel, Eliaz and Rozen. In both cases the constraints in the number of products that can be considered by consumers create incentives for firms to use prices as an instrument to influence the products considered by consumers.[5]

Finally, my work and results relate to the literature on switching costs. Dube, Hitsch and Rossi (2009) show that switching costs can decrease equilibrium prices in a dynamic model of price competition. They point out that switching costs have two effects that work in opposite directions: (1) a "harvesting" effect that creates incentives for a firm to raise the price to "harvest" the existing consumer base, and (2) an "investment" effect that increases the incentives of a firm for decreasing the price to raise a loyal customer base and prevent consumers from switching. Dube, Hitsch and Rossi (2009) find that the magnitude of the "investment" effect is larger than the magnitude of the "harvesting" effect for intermediate values of switching costs.

The paper proceeds as follows. Section 2 presents the demand and supply model. Section 3 describes the estimation strategy and the data. Section 4 presents the results and discusses their implications for consumers and firms. Section 5 evaluates the effects of varying the marginal search costs for only one product. Section 6 concludes the paper.

[5]These ideas are closely related to Eliaz and Spiegel (2011)'s model in which firms use costly marketing devices to influence consideration sets. In a related paper, Dinerstein, Einav, Levin, and Sundaresan (2014) explore the role of search design on transaction prices and price dispersion.

2 Model

This section presents a model that captures some of the patterns observed for shopping and purchase behavior on shopping trips and purchases of liquid laundry detergent (laundry detergent hereafter). These patterns are described in Pires (2015), where I find evidence consistent with costly search. I show that (i) non-detergent expenditure and knowledge of a store affect the likelihood of purchasing detergent, and (ii) marketing devices and time elapsed since the last purchase affect brand choice conditional on purchasing detergent. Non-detergent expenditure and knowledge of a store should not affect the preferences for consuming or purchasing detergent, but they may affect the cost of going to the detergent aisle.[6] I therefore interpret the correlation between these variables and the purchase decision as evidence for the presence of fixed costs of searching. Likewise, if marketing devices do not affect preferences, the observed correlation between these devices and brand choice is consistent with the presence of search costs and a positive effect of marketing devices on these costs. Finally, the negative relation between the time elapsed since the last purchase and conditional brand choice is consistent with nonsequential costly search. Nonsequential costly search creates a positive correlation between inventory and the likelihood of buying the favorite brand conditional on purchasing detergent. Consumers are less likely of buying detergent when inventory is high. The benefits of searching therefore fall with inventory, which creates a positive correlation between inventory and the number of searched products if consumers incur costs to search each product. Hence, the likelihood of choosing the favorite brand when a purchase occurs is increasing in households' inventory because there are less alternative options among the searched options when inventory is high but the favorite brand is almost always among the searched products. I further show that there exists a large price variation across products and over time within the same product, which creates a natural economic motive to search.

[6] A potential complementarity between laundry detergent and other goods could also explain the positive correlation between the likelihood of buying detergent and the non-detergent expenditure. I, however, believe that this is not the explanation for the observed correlation, because there are very few complementarities between laundry detergent and the other goods that can be purchased during a shopping trip. Even if there was such complementarity, there is no reason for purchases of laundry detergent and of potential complementary goods occur during the same shopping trip, because laundry detergent is a storable good.

Non-detergent expenditure may also affect demand for detergent through the budget constraint. Yet, the results suggest this channel is either not important or dominated by the channel I am proposing, because the budget constraint channel would imply a negative correlation between demand for detergent and non-detergent expenditure, but I find a positive correlation

2.1 Demand

The modeling assumptions are as follows. When a consumer[7] enters a store, she knows the products available but does not know the price or the realization of the random shocks associated with each product. The random shocks include time-varying product characteristics such as temporary changes in product packaging and labelling, product prizes and premiums.[8] The temporary nature of these product characteristics makes that consumers only become aware of them at the store. To buy and obtain the information about the price and realization of the random shocks for a specific brand j of size x the consumer needs to pay a cost sc_{jxt}.[9] Consumer pays a fixed cost $\bar{S}_t$ if she searches at least one product. Search costs therefore include both the costs consumers incur to find out about the characteristics of a product and shopping costs.

Choice is modelled as a two-stage process. In the first-stage, after entering a store, the consumer decides whether to search. If the consumer does not search, she does not have to make another decision in the current time period. If the consumer searches, she will choose the set of products to search. In the second stage, after observing the price and the random shocks for the searched products, the consumer chooses whether to buy one of them. I will refer to the first stage as the "search stage" and the second stage as the "purchase stage". I assume the timing and incidence of shopping trips are exogenous.

The model considers a fixed sample size search process where consumers commit to a fixed number of searches before the beginning of the actual search. In this process the search only finishes after the consumer searched the products she committed to, even if she gets a good search outcome early on. The assumption of a fixed sample size search process is supported by empirical evidence in favor of a fixed sample search strategy over a sequential search strategy.[10]

I define a product as a brand-size combination. Let Ω_{sxt} be the set of brands of size x available in store s at period t and let Λ_{sxt} be the powerset of Ω_{sxt} excluding the the choice of not searching.

[7]The unit of observation in my data is a household and this is the relevant consumer in my application. I use "consumers" and "households" interchangeably.

[8]Prizes are promotional items (e.g., small toys, collectibles, and other small items) found in packages or available from the retailer at the time of purchase that are included in the price of the product at no extra cost.

[9]The inclusion of a cost of searching each product is supported by empirical evidence suggesting that consumers do not search all products, even after walking into an aisle. Pinna and Seiler (2013) report path-tracking evidence of this data pattern.

Marginal search costs that are affected by product display and feature ads further provide a justification for why firms use these marketing devices.

[10]In the Online Appendix I show that (1) the prices of brands that are not the favorite brand (defined as the most frequently purchased brand in the sample) affect the likelihood of purchasing the favorite brand even when the favorite brand is on sale, (2) the likelihood of buying the favorite brand falls with an exogenous and unexpected decrease in the prices of all brands when the depth of the price discount of brands that are not the favorite is larger, (3) the effect of the prices of the favorite brand on the incentives to continue searching after observing the price of the favorite brand is not significant, and (4) there is a negative correlation between price dispersion and search costs both within and across stores. All of these patterns are expected when consumers follow a fixed sample size search strategy but usually cannot be explained by a sequential search strategy. See De los Santos, Hortacsu and Wildenbeest (2012) and Honka (2014) for a discussion about the sequential and fixed sample size search processes.

Define $\Lambda_{st} \equiv \cup_x \Lambda_{sxt}$. In each purchase occasion a consumer can buy at most one product. The value obtained by consumer i in period t from purchasing brand j with size x is

$$U_{ijxt} = \alpha_i p_{jxt} + \eta \left(\max \{I_{it-1} + x - C_{ixt}, 0\}\right)^2 + \xi_{ijx} + \epsilon_{ijxt} = \delta_{ijxt} + \epsilon_{ijxt}$$

where p_{jxt} is the price of brand j of size x at shopping occasion t, I_{it-1} is the current inventory, C_{ixt} is the consumption at period t if consumer purchases quantity x,[11] ξ_{ijx} is a brand-size specific effect on utility that could vary across households, and ϵ_{ijxt} is a random shock to consumer brand-size choice.[12] The value of purchasing nothing is

$$U_{i0t} = \eta \left(\max \{I_{it-1} - C_{i0t}, 0\}\right)^2 + \epsilon_{i0t} = \delta_{i0t} + \epsilon_{i0t}$$

I assume consumers are myopic and thus they do not take into account the effect of their current choices in the future value of inventory, even though the value of inventory affects the current utility.[13] The evolution of inventory is described by $I_{it} = I_{it-1} + x_{it} - C_{it}$; where x_{it} is the quantity purchased at period t, and C_{it} is the consumption at period t.

The expected net benefit of searching the set K, denoted by V_{iK}, is the difference between the expected maximum utility of searching the brands in the set K and the cost of searching these brands. That is,

$$V_{iK} = E\left[\max_{j \in K} \{U_{ijt}\}\right] - SC_{iKt}$$

where SC_{iKt} is the cost of searching the set K at shopping occasion t. The total search costs include a fixed component $\bar{S}$ and a specific cost sc of searching each product in the consideration set. That is,

$$SC_{iKt} = \bar{S}_{it} + \sum_{l \in K} sc_{ilt}$$

The proposed model does not allow me to identify the baseline search cost separately from the intrinsic quality of the products for an additive specification. I take that into account in the choice of the functional forms for the search costs. I assume that the fixed search cost $\bar{S}$ is $\bar{S}_{it} = \tilde{S}_i \cdot \exp\left(z_{it}^{s\prime}\beta^s\right)$; where z^s are the covariates that affect the fixed search cost and $\tilde{S}$ and β^s are parameters to be estimated. For sc I assume that $sc_{ilt} = \tilde{s}_i \cdot \exp\left(z_{ilt}^{g\prime}\beta^g\right)$; where z^g are the

[11] The inclusion of inventory in the utility specification captures the effects of storage costs and potential effects of inventory on consumption. In the estimation I include a quadratic term for inventory in the utility specification because the linear effect of inventory reflects essentially differences between the purchased size and this is captured by the brand-size fixed-effects.

[12] The prices and the nonprice attributes are store specific. The idiosyncratic tastes and the random shocks can also be store specific. I omit the store subscript from those variables to simplify the notation. Likewise, in the specification for search costs, display and feature ads are store specific but the subscript for the store is omitted.

[13] Hendel and Nevo (2006) and Pires (2015) show that the dynamic effects of consumer inventory and stockpiling can be important and thus future research should explore the dynamic effects created by consumer inventory. Likewise, it would be important to evaluate the potential dynamic effects associated with learning about prices.

covariates that affect marginal search costs and $\tilde{s}$ and β^g are parameters to be estimated. I assume that the fixed cost of searching $\bar{S}$ is a function of non-detergent expenditure and the specific cost sc of searching a product is a function of product display and feature ads. I further assume $\tilde{S}_i$ and $\tilde{s}_i$ vary with household income and household size.

In the search stage consumers face uncertainty about the actual prices and the random shocks to consumer choices. Although consumers do not observe actual prices before searching, it is possible that they receive some signal about those prices before the search process starts and this signal can affect the formation of their price beliefs. For instance, consumers will update their price beliefs according to the level of marketing activity that they observe if there is a positive correlation between prices and the marketing activities associated with a product. Suppose firms advertise more their products during a price promotion, then consumers will believe that it is more likely a lower price when they observe advertisement, thus creating a positive correlation between consumers price beliefs and actual prices. It is important to distinguish the aforementioned effect from the effect of marketing activities on search costs. In the aforementioned situation marketing activities do not reduce search costs because their content neither provides information about what consumers are going to find after search nor reduces the searching effort. The effect of marketing activities is through the effects on beliefs that can be correct or wrong (i.e., in some situations consumers find that a product is not on sale even though it was advertised).

Another mechanism through which consumers can get information about actual prices is word-of-mouth. Consumers can get information about the actual price from other consumers, but that information may be imprecise. For instance, the information may just be that the product is at a good or bad price, without specifying the exact price or even the reference point to classify a price as good or bad.

I do not observe how consumers form their price beliefs and thus I do not know the relation between actual prices and consumers' price beliefs. It is indeed possible that price beliefs do not depend on actual prices, but it is also possible that consumers have full information about prices. In order to evaluate what happens under different situations I assume consumers price beliefs in period t are characterized by a distribution with all mass in $(1-\lambda)\,\bar{p}+\lambda p_t$ where $\bar{p}$ is the sample mean of prices and $\lambda \in [0,1]$. I estimate and recover the structural parameters for different situations by varying the value of λ, which allows me to consider several hypothesis about consumers' expectations. My estimation procedure does not identify λ and only allows me to say how the model fits the data for different values of λ. The evaluation of the fit of the model for different values of λ can nevertheless be useful, because it allow us to evaluate whether some values of λ are rejected by the data, for instance, if the model can only match the data by producing unrealistic results.

As for the random shocks to consumers' choices, I assume they are independent and identically distributed extreme value type I. I further assume prices are independent of the random shocks to consumers' choices.

Finally, I add a mean-zero stochastic noise term ς_{iK} to V_{iK} to smooth the choice set probabilities (De Los Santos, Hortacsu and Wildenbeest 2012). I assume ς's are independent and identically distributed extreme value type I.

2.2 Supply

For the supply side I assume each product is produced by a different single-product firm.[14] The subscript l is used to denote both the product and the firm that produces it. The profits of firm l are:

$$\pi_l = (p_l - c_l)\, M \cdot s_l(p) - C_l$$

where $s_l(p)$ is the market share of product l, which is a function of the vector of prices p, M is the size of the market, p_l is the price of product l, c_l is the marginal cost of product l, and C_l is the fixed cost of production. I assume that (1) firms play according to a Nash-Bertrand equilibrium, (2) there exists a pure-strategy Nash-Bertrand equilibrium in prices, and (3) the prices that support it are strictly positive.

Although demand depends on the inventory hold by consumers, I assume that firms cannot observe or track consumers' inventory and make their choices assuming that the inventory of each consumer is equal to the median inventory. I further assume that firms do not take into consideration the evolution of inventory level when choosing prices and therefore solve a static problem. As pointed out by Osborne (2014), this can be interpreted as a form of rational inattention, where the marginal cost of gathering information about last period's inventory is very high. Another potential interpretation of this assumption is that firms receive a new group of households every week. These assumptions are consistent with some anecdotal evidence that firms are not aware of consumers' current inventory and thus their decisions are not based on this variable.

3 Data and Estimation

My empirical strategy uses household panel data for shopping trips and purchases of laundry detergent[15] collected by Information Resources Inc. (IRI). The data are drawn from two behavior scan markets (Eau Claire, Wisconsin; and Pittsfield, Massachusetts) and cover six years (313 weeks), beginning January 1, 2001. I supplement the panel data with aggregate store level data,

[14] I therefore assume that prices are set by product divisions of the manufacturer rather than by the retailer or centralized multiproduct manufacturers.

[15] Households usually purchase only one package of laundry detergent during a shopping trip and therefore the discrete choice assumption of the model is satisfied. Other product categories do not satisfy this condition and this is one of the reasons for using laundry detergent in my empirical application. Households purchase only one package of detergent during a shopping trip, but they can choose among different package-sizes. Hence, stockipiling is done through the purchase of different sizes.

which include the average price charged, the aggregate quantity sold, and the promotional activities (product display and feature ads) for each product at each store during each week. The store level data are also collected by IRI.

The raw data were cleaned to guarantee a suitable sample for the estimation. An observation in the final sample is a shopping trip. The final sample consists of 46,731 observations. It contains 697 households, 23 stores, and 232 UPC's, aggregated into 32 brands from 16 different manufacturers. A detailed description of the data and the procedures to clean the raw data are provided in the Online Appendix.

The empirical strategy consists of a "front-end" estimation of demand and cost parameters and a "back-end" analysis to evaluate the equilibrium prices and calculate the profits for different search costs (see Nevo, 2000; and Nevo, 2001). I first estimate the demand and search cost parameters by maximizing the likelihood of choices implied by the proposed demand model. I then recover marginal costs from the profit maximization first order conditions using the demand and search cost estimates jointly with pricing rules implied by a Nash-Bertrand pricing game. Finally, I use the demand and cost estimates to evaluate numerically the equilibrium prices of all products for different values of search costs. I then calculate the profits associated with these equilibrium prices.

The demand and search costs parameters are estimated by maximizing the likelihood of observed choices.[16] This likelihood is characterized by $\log L = \sum_{j,x} d_{jxt} \ln P_{jxt}$;[17] where the probability of choosing brand j of size x in shopping occasion t is

$$P_{jxt} = \sum_{K \in \Lambda} P_{jxt|K} P_K$$

and the probability of choosing brand j of size x in shopping occasion t conditional on searching set K and the probability of searching set K are, respectively,

$$P_{jxt|K} = \frac{\exp\left(\delta_{jxt}\right)}{\sum_{(m,z)\in K\setminus\{0\}} \exp\left(\delta_{mzt}\right)}$$

$$P_K = \frac{\exp\left(V_K\right)}{\sum_{L\in\Lambda\cup\{\phi\}} \exp\left(V_L\right)}$$

One of the estimation challenges is that I do not observe the products searched by households and therefore need to integrate over all possible consideration sets. This strategy creates a complex combinatorial problem with a large number of products. To make the problem tractable, I make the following assumptions. First, products can be aggregated into ten brands: Tide, Xtra,

[16] The identification of the utility and search cost parameters follows the same arguments discussed in Pires (2015).

[17] To simplify notation I omit the subscript i in this section.

Dynamo, Purex, All, Arm&Hammer, Era, Wisk, a Private Label, and a composite brand that includes all the other brands. Second, each product can be assigned to one of three sizes: small, medium, and large.[18] Finally, consideration sets only include products of the same size. The number of potential consideration sets is 3069.

Other estimation challenge is that I do not observe inventory or consumption decisions. The estimation of inventory holdings follows Hendel and Nevo (2006). For each household, I start with an initial guess for inventories and then calculate the inventory in each week using the observed purchases and the estimated consumption. To reduce the impact of the initial guess, the first 8 visits of each household are used to simulate the distribution of inventories, but are not used in the estimation.

To simplify the estimation procedure, I assume households are consuming detergent at a constant rate γ until they run out. I calculate the consumption rate as follows. I start by assuming the rate of consumption for each household is the weekly average purchases during the first 52 weeks. This initial guess therefore ignores the possibility of stock-outs. I then simulate the inventory in each week assuming that my guess for the consumption rate is the true consumption rate and calculate the number of weeks with no consumption in this simulation. I update the consumption rate correcting for the number of weeks with zero consumption (in the simulation). I repeat the previous procedure with the updated consumption rate until the difference between the consumption rate used to simulate inventory and the updated consumption rate is sufficiently small. I can recover the rate of consumption because I observe households over a long period of time. There is, however, some measurement error in the estimation of the consumption rate, but I believe that the measurement error is small as I observe several purchases for each household and the consumption rate is consumer-specific.

4 Results

4.1 Demand

Table 1 reports the demand and search cost estimates for a static demand model with costly search. Each column reports estimates for specifications that differ with respect to the effect of actual prices on consumers' price beliefs. Specifications are ordered according to the level of correlation between consumers' price beliefs and actual prices. Hence, the first specification assumes actual prices do not affect consumers' price beliefs, whereas the last specification assumes full information about prices.

The results show that marginal search costs are statistical and economically significant for all

[18]Products with size greater than 0 and lower than 4lb were assigned to the small size, products with size greater than 4lb and lower than 8lb were assigned to the medium size, and products with size greater than 8lb were assigned to the large size.

specifications. Moreover, marginal search costs are higher for households with a larger income, which may account for a higher opportunity cost of time for these households. The monetary value of search costs seems to be higher for specifications that assume a higher correlation between consumers' price beliefs and actual prices. The intuition for this result is that, with more information about prices, the model requires higher estimates of search costs to fit the presence in the data of shopping trips where consumers miss price promotions and do not purchase the good. My estimates of search costs include, among others, the cost of collecting information about the price and characteristics of the product, the time spent to find a product in the shelves, mental storage, and processing costs. They further include the opportunity cost of choosing not to search (i.e., the benefits of searching predicted by the model that consumers lose when they choose not to search). This opportunity cost tends to be higher when information frictions are lower.

Product display and feature ads reduce considerably the cost of searching a product. For instance, the cost of searching a product that is displayed and featured is less than two thirds of the cost of searching a product that is neither displayed nor featured for most of the specifications. My goal in this paper is to evaluate the effects of marginal search costs on equilibrium prices and profits. These results therefore reveal that this evaluation allows us to understand the importance of product display and feature ads for profits and prices.

The fixed search costs and the price-coefficient constant are significant and have the expected direction. The magnitude of the price coefficient falls with respect to the level of correlation between consumers' price beliefs and actual prices. Table 2 reports the demand elasticities obtained from the estimates in table 1. Demand elasticities[19] fall with the level of price information for almost all products, but they increase in some cases for the three top products (i.e., medium packages of Tide, Xtra, and Purex), the medium-package of All and of the composite brand, particularly for low levels of correlation between actual prices and consumers' price beliefs. The fall in elasticities for most of the products is explained by the fall in the price coefficient parameter. However, search cost estimates are higher for higher level of price information, which reduces consideration-set size. More information about prices can therefore reduce the market power of top products derived from limited information, which explains the raise in elasticities for some popular products for low levels of λ.

The estimates presented in table 1 are used to recover the marginal costs in each shopping trip. The estimates for the marginal costs are reported in table 3. Assuming that actual prices do not affect consumers' price beliefs yields some unrealistic marginal costs[20] for 2 products– medium packages of Xtra and Purex. These unrealistic values for the marginal costs of the medium packages of Xtra and Purex are necessary for the model explaining the low prices of these

[19] Interpretation of the demand elasticities considers the absolute value of the estimates

[20] Peters (2006) points out that "it may be more appropriate to refer to [the value recovered from the first-order condition] as the supply-side residual rather than as marginal cost", because its value may reflect prediction errors due to misspecified conduct.

products when they have a large market power due to consideration sets. The other specifications yield reasonable patterns and values for marginal costs. These results suggest that consumers have some information about actual prices and thus the assumption that actual prices do not affect consumers' price beliefs is not the best one.

4.2 Supply

In this section I evaluate the effect of search costs on equilibrium prices and profits. The demand estimates reveal that firms can employ marketing instruments to affect search costs and consequently consumer welfare. Hence, the identification of the effects of search costs is an important economic question. It is also an empirical question, because search costs create incentives that work in opposing directions. On the one hand, search costs create an "investment" incentive for a firm to lower prices so that it can reduce consumers' beliefs about its prices and prevent consumers from not searching. On the other hand, search costs create a "harvesting" incentive for a firm to raise prices, because they reduce the number of products that consumers search, which allows each firm to extract rents from consumers with a greater preference for its product. In short, search costs increase the competition to be present in consumers' consideration sets, but they reduce the competition within the consideration set.

The aforementioned "investment" incentive depends on whether and how actual prices affect consumers' price beliefs. For instance, if actual prices do not affect consumers' price beliefs, larger search costs will not create an "investment" incentive. It is, however, possible that a firm lowers its prices with an increase in search costs if this increase reshuffled the preferred consideration sets of consumers such that the probability of searching a product became higher. Also, higher search costs may lower prices by increasing the relative importance of consumers with more elastic demand in the profit of a product.[21]

The effect of search costs on profits is an empirical question, even without an "investment" incentive or a fall in prices. Larger search costs reduce price competition by lowering the number of searched products, but they also decrease the probability of searching.

There is an analogy between the effects of search costs in my model and the effects of switching costs (see for example, Dube, Hitsch and Rossi, 2009; Cabral, 2013). There are, however, some differences between the effects of search costs and switching costs. First, in my framework firms do not solve a dynamic problem and thus the "investment" incentive occurs through price beliefs and their effects on consideration-set formation rather than through the dynamic gains from raising the loyal customer base. Hence, in a model with search costs the benefit from reducing the price is only for the current shopping trip and the magnitude of the effect may therefore be lower than in a switching cost model in which the "investment" incentive is applied to a repeat-purchase context.

[21] See Moraga-Gonzalez et al. (2014) for a discussion of this mechanism.

Second, in a search model there is not an existing customer base and thus the "harvesting" incentive refers to consumers with stronger preferences for the brand, which is captured by ξ in the model. Finally, switching costs create a vertical differentiation among products, whereas in my model search costs do not create vertical differentiation. The only differentiation created by search costs is against the outside option, because the value of the outside option increases with search costs.

In the next subsections I evaluate the effect of search costs for different levels of information regarding actual prices. I start by considering a situation where actual prices do not affect consumers' price beliefs. I next consider the other extreme case in which consumers have full information about actual prices. Finally, I summarize the results for some situations where consumers receive some signal about actual price but the signal is not completely informative.

4.2.1 Equilibrium prices and profits when actual prices do not affect consumers' price beliefs

In this subsection I evaluate the equilibrium prices and profits for different search costs when actual prices do not affect consumers' price beliefs. Figures 1a and 2a plot, respectively, the equilibrium prices and the equilibrium price indexes of 6 products with respect to search cost. The figures also plot the equilibrium average price and the respective index. These figures show that larger search costs increase prices when actual prices do not affect consumers' price beliefs. The "harvesting" incentive is therefore the dominant effect. The results are further explained by the absence of an "investment" incentive.

Although larger search costs increase the prices of all products, there is a large heterogeneity across products regarding the magnitude of this effect. The effect is small for products with low market shares, but large for products with high market shares. For instance, the price of the medium-package Purex with a search cost parameter equal to 6 is nearly twice the price with a zero marginal search cost. The intuition for these results is as follows. High-market-share products are the preferred products for most of the consumers and thus are the last products that they stop searching for. The elasticity of substitution is therefore disproportionately reduced for high-market-share products when search costs increase, which implies that the probability of choosing these products conditional on searching rises and becomes less sensitive. In contrast, the harvesting incentive for low-market-share products is lower, because they have a smaller customer base and higher price elasticities. The differences relative to high-market-share products indeed increase with search costs. Higher search costs make consumers with less elastic demand stop searching for low-market-share products, thereby increasing the average elasticity of consumers searching these products. This numerical result has similarities with the analytical result in Arie and Grieco (2014) that the "harvesting" incentive of larger switching costs is stronger for high-market-share firms.

The smaller increase in prices of low-market share products with higher search costs is further explained by a change in the composition of consumers' consideration sets. As consumers attribute higher valuations to medium-size products, these products have higher market shares and thus their prices are more sensitive to search costs variations. Hence, some consumers–particularly consumers who are more price sensitive–move their search efforts from medium-size products to small- and large-size products for larger search costs. In fact, in my empirical application the probability of searching a small-size product increases with marginal search costs when their level is low or moderate. Hence, the smaller increases in prices for small packages is partly explained by an incentive for lowering prices with a rise in marginal search costs to induce a purchase from the new consumers searching the product. Moreover, most of these new consumers searching the product have high price elasticities–as their switch in the searched products is driven by the larger increase in prices of high-market-share products–which increases even more the incentives for lowering prices.

Figure 3a and 4a plot, respectively, the profit and the profit indexes of 6 products for different values of search costs. Total profits are also plotted. The figures show that total profits initially rise and then fall for larger search costs. This pattern is also observed for the other products plotted.

Search costs affect profits through prices and demand. The equilibrium prices always rise for larger search costs, but the effect on demand can be either positive or negative. Hence, the profits of a product can rise for larger search costs because the price and the demand increase or the gains with the rise of prices outweighs the losses from a fall in demand. In the latter case, the larger search costs allow firms to extract rents from consumers and these gains are higher than the losses created by the smaller consumer base.

The previous reasons explain why the profits of some products rise with larger search costs for low and moderate levels of search costs. I next explain why the profits of all products fall with larger search costs for high levels of those. The intuition is as follows. The "harvesting" gains from larger search costs have an upper bound because consideration sets include at most one product after a certain level of search costs. Hence, the competition faced by a product does not fall with larger search costs for high levels of those and thus the incentives of raising prices and the potential for increasing demand disappears.

Table 1 shows that in my application the marginal search cost for the median household is 3.92 when actual prices do not affect consumers' price beliefs and products are neither displayed nor featured and 2.21 when products are displayed and featured. Figures 3a and 4a show that total profits and the profits of the other 6 products are higher when products are displayed and featured. In particular, total profits with all products displayed and featured are more than three times higher than the total profits when products are neither displayed nor featured. Employing displays and feature ads would be beneficial for consumers due to a fall in prices, in addition to the lower search costs. For instance, the price of the medium package of Purex would drop from \$4.33 to nearly \$3.68 when all products are displayed and featured.

In order to illustrate how displays and feature ads disproportionately affect prices and profits for certain types of products, I plot the market share and the effect of displays and feature ads on prices for each product in figure 5a and the effect of displays and feature ads on profits for each product in figure 6a. Figure 5a shows a sharp negative correlation between the market share of a product and the respective fall in price with displays and feature ads. The price fall is at most 1.6% for products with a small market share, and it is at least 8% for the top 6 products. As for profits, there is a large positive correlation between the market share of a product and the respective rise in profits with displays and feature ads. Tables 4 and 5 report the correlation of size and market-share with, respectively, the effect of displays and feature ads on price and profit. These tables suggest that the heterogeneous effects are essentially associated with differences in market shares.

4.2.2 Equilibrium prices and profits with full information about prices

In this subsection I evaluate the equilibrium prices and profits for different search costs when consumers know the actual prices. Although consumers have complete information about actual prices, I still assume that consumers do not know the realization of the random shocks associated with each product and collecting that information is costly.

Figures 1d and 2d plot, respectively, the equilibrium prices and the equilibrium price indexes of 6 products and the average price for different values of the search costs. The figures reveal heterogeneous effects across products. For some products–such as the small package of Tide–the equilibrium prices initially rise and then fall for larger marginal search costs. In contrast, for other products–such as the medium packages of Tide and Purex–the equilibrium prices always fall for larger marginal search costs. For the average price we observe the latter pattern.

The figures further show that the effects of larger search costs on prices are small for most of the products. The coexistence of two incentives–the "investment" and the "harvesting" incentive–that work in opposite direction explains the aforementioned results. My results indeed suggest that these two incentives cancel each other out for most of the products, which explains the small effects of larger search costs.

Figures 1d and 2d suggest that the effects of search costs on equilibrium prices are higher for products with larger market shares.[22] Although the "harvesting" incentive is stronger for high-market-share products, the "investment" incentive is also larger for these products with complete information about prices, because they have higher expected utility, are more likely to be in the consideration set, and have a higher choice probability conditional on consumers searching them.

[22]The medium packages of Tide and Purex are the two products among the 6 in the figure with the larger market shares and they are also the products with the larger effects.

The gains of being included in the consideration set are higher for these products and thus they have more incentives to reduce prices.

Figures 3d and 4d plot, respectively, the profit and the profit indexes of 6 products and the total profits with respect to search costs. The relation between profits and search costs is characterized by an inverted U-shaped function for some products, but there are products for which the profits always fall with larger search costs. The potential increase in profits with larger search costs is smaller than in the situation with no information about prices. Some products have nonetheless substantial increases in profits with a rise in search costs. For instance, profits of the small packages of Tide and All increase by nearly 25% when search costs rise from 0 to 1.2 utils.

Table 1 and the results of this subsection suggest that firms have higher profits when products are displayed and featured (ignoring the cost of displays and feature ads). In contrast, displays and feature ads can be bad for some consumers, because the prices of some products are higher with displays and feature ads. For instance, the price of Purex is nearly \$0.07 higher with displays and feature ads. The average price is indeed \$0.01 higher with displays and feature ads. If this negative effect of higher prices for some products is higher than the savings in search costs, then the welfare of some consumers can decrease with displays and feature ads.

Figure A1 in the Online Appendix reports the expected net utility[23] with respect to search costs. The figure shows that the expected net utility always falls for larger search cost: the fall in the prices of some products is not enough to compensate the losses due to the larger search costs and the larger prices of some products. The suggested measure for the expected net utility integrates over all consumers and therefore the results in figure A1 are reconcilable with the possibility that the expected net utility of some groups of consumers rises for larger search costs.

Figure 5d plots the market-share and the effect of displays and feature ads on price for each product. The figure shows that the correlation between the market share of a product and the effect of displays and feature ads on the price of that product is positive, which contrasts with the results when there is no information about actual prices. The effects of displays and feature ads on price are small, but there exists a large heterogeneity, which looks correlated with market share. In particular, displays and feature ads lower the price of a product with low market share, but they raise prices for products with high market shares. For the top 4 products the rise in prices is indeed more than 1 percent.

4.2.3 Equilibrium prices and profits with partial information about prices

This subsection evaluates the effects of search costs when consumers receive some signal about actual prices before searching but they do not have complete information about those prices. In particular, I assess how the level of information provided by the signal affects the results.

[23]The expected net utility is defined as $EU = \int \max_k \{V_{ik} + \varsigma_{ik}\} \, dF(\varsigma) di$

Figures 1 and 2 suggest that a rise in the information provided by the signal increases the magnitude of the "investment" incentive, which reduces the rise in prices with search costs. In fact, the investment incentive can be stronger than the harvesting incentive when the signal received by consumers about actual prices is very informative. For instance, panel (c) shows that the price of the medium package of Purex slightly falls with search costs when search costs are already very high and $\lambda = 0.7$.

The results further reveal that a lower price of one product can create a positive externality in other products that are usually searched together by making consumers choose consideration sets with those products.

Figures 3 and 4 show that the relation between profits and search costs is characterized by an inverted U-shaped function for some products, whereas for other products profits always fall. This pattern is valid for different values of the signal. The figures, however, suggest that the positive effects of search costs on profits fall with the level of information that consumers have about actual prices. A rise in the information about prices induces firms to compete more fiercely during the consideration-set formation stage, which has negative effects on profits. The potential market power created by search costs is therefore lower when information frictions are lower.

Figures 5 and 6 explore the heterogeneous effects of displays and feature ads on, respectively, prices and profits. Figure 5 shows that the effect of displays and feature ads on price is usually correlated with the product market share, but the direction of this correlation depends on the level of information about prices. In particular, for low values of λ there is a negative correlation, whereas for high values of λ the correlation may be positive. These results further suggest that the effect of displays and feature ads on the price of high-market-share products is very sensitive to the value of λ: for low values of λ there is a large fall in prices, whereas for high values of λ there can even exist a rise in prices.

5 Extensions

In this section I evaluate the effects on equilibrium prices and profits of variations in the search costs of one product. In particular, I evaluate the effects of larger search costs of the medium-package Tide while holding constant the search costs of the other products. As pointed out by Wilson (2010), models with endogenous search costs can yield asymmetric search costs and thus it is important to allow for this possibility.

Figures 8 and 9 report, respectively, the equilibrium price indexes and the equilibrium profit indexes with respect to the cost of searching the medium-package-Tide for different values of λ. The results in these figures assume that all products, except the medium-package Tide, have a zero search cost.

Figure 8 shows that the price of the medium-package Tide rises with its search costs when actual prices do not affect consumers' price beliefs, but it falls for all the remaining cases. If actual prices do not affect consumers' price beliefs, then the price of the medium-package Tide can only be used to "harvest" the consumers who still search this product despite the higher search costs.[24] In contrast, the price of the medium-package Tide can be used to induce consumers to search it if consumers receive some informative price signal. Our results reveal that this incentive is larger than the "harvest" incentive and thus the prices of the medium-package Tide fall with larger search costs. The magnitude of this fall increases with the level of information about actual prices, because a reduction in prices to attract consumers becomes more effective.

Figure 8 further reveals that a larger search cost of the medium-package Tide affects mostly the other medium-size products, particularly when consumers have less information about prices. The prices of small- and large-size products always rise with larger search costs of the medium-package Tide, but the prices of the medium packages of Purex and Arm fall when consumers have complete information about prices. The prices of these two products nevertheless rise with larger search costs of the medium-package Tide in the remaining cases that are plotted in figure 8.

A larger search cost of the medium-package Tide creates incentives for searching other products instead of Tide. As consumers search only products of the same size, it is, however, possible that a large search cost of the medium-package Tide makes consumers move their search efforts from medium-size products to small- or large-size products. It is further possible that a larger search cost of the medium-package Tide makes consumers not search at all, but that is unlikely. Hence, for small- and large-size products a larger search cost of the medium-package Tide increases the number of potential consumers, but does not affect the competition within the consideration sets in which they are present. The prices of these products therefore tend to increase with larger search costs of the medium-package Tide. The rise in the price of these products is higher for larger values of λ, because the fall in the prices of medium-size products moves consumers who are more price sensitive from small- and large-sizes to medium-sizes. As consumers who search small- and large-sizes with higher search costs are less price sensitive, then small- and large-package products have another incentive to rise prices.

Medium-size products other than Tide compete with the medium-size of Tide within the consideration set. So, these products have incentives to reduce their prices when the price of the medium-package Tide falls. Moreover, these products may have incentives to reduce their prices when the search cost of the medium-package Tide increases to provide incentives for searching medium-size products. These incentives are larger for higher levels of correlation between actual prices and consumers' price beliefs.

Figure 9 shows that larger search cost of the medium-package Tide lead to (i) a fall in the profits of the medium-package Tide, and (ii) a rise in the profits of small- and large-size products.

[24] The creation of search costs by the medium-package Tide makes consumers less willing to search this product, thus softening competition and creating incentives for other firms rise prices (Wilson 2010). This also explains the increase in prices of the medium-package Tide with no information about prices.

These results hold for all values of λ, even though the rise in the profits of small- and large-size products is larger for low values of λ. In contrast, the effects of the search costs of the medium-package Tide on the total profits of the other medium-size products depend on the value of λ: total profits and the profits of the other medium-size products rise with medium-package-Tide search costs for low values of λ, but they fall when λ is high. These effects are nevertheless small.

The rise in the search costs of the medium-package Tide reduces the likelihood of searching and purchasing this product, thus lowering its profits. Furthermore, in the situations described in panels (b) to (d) a larger search cost of the medium-package Tide is associated with lower prices of this product, which reduces profits. In panel (a) the price of the medium-package Tide rises with its search costs, but the losses from the lower demand are higher than the gains from raising prices.

The effects of the search costs of the medium-package Tide on the demand of medium-size products other than Tide can be either positive or negative. On the one hand, there is a reduction in the competition within the consideration set. On the other hand, some consumers move their search efforts from medium-size products to small- and large-size products. Furthermore, the prices of these products rise with the search costs of the medium-package Tide in panels (a) to (c), but they fall with full information about prices.

Figure 9 further shows that total profits can rise with larger search costs when consumers have little or no information about actual prices. Hence, limited information and costly search can create market power and yield larger profits.

6 Conclusions

In this paper I evaluate the impact of search costs on equilibrium prices and profits in a real-world setting using a structural model of demand and supply. I find that the profits of some products initially rise and then fall for larger search costs. This effect of search costs on profits implies that for some products it is optimal to have an intermediate level of search costs rather than zero search costs (or high search costs). Firms may therefore create search costs or avoid engaging in activities that reduce them to zero. Nonetheless, all firms are worse off when search costs are large and thus gain from avoiding high levels of search costs. My results further suggest that the positive effects of search costs on the profits of some products are lower when consumers have more information about actual prices.

I find that the effects of search costs on equilibrium prices depend on whether a firm has an "investment" incentive for reducing the price. If actual prices do not affect consumers' price beliefs, prices will always rise with larger search costs. In contrast, if consumers receive a signal sufficiently informative about prices, then the "investment" incentive can be stronger than the "harvesting" incentive and a rise in search costs reduces the prices of some products. These results therefore provide important insights for regulators, competition authorities, and antitrust agencies. They show the importance of knowing the magnitude of search costs and the level of information regarding prices to design welfare maximizing policies. The findings further suggest that the level of search costs and information available should be taken into account by the Department of Justice (DOJ) and the Federal Trade Commission (FTC) when negotiating merger remedies.

My results illustrate that the relation between actual prices and consumers' price beliefs has important implications in the effects of marginal search costs on prices and profits. Future research should explore the mechanisms through which consumers form their price beliefs and evaluate the effects of these mechanisms for firms.

In my analysis I look at the supply side from the perspective of manufacturers. Retailers are multiproduct product firms and therefore will have different incentives from the single-product firms analyzed in this paper. In this paper I avoid questions of manufacturer-retailer relationships and vertical contracts to keep the analysis simple and focus the attention on the role of search costs. This is one of the limitations of my analysis and the comparison of the incentives of manufacturers and retailers is an important question that should be answered in future research. In some cases nonlinear vertical relationships, anyway, allow manufacturers to obtain the retail prices they want (Bonnet and Dubois 2010), which allows me to generalize my results to a broader set of situations.

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Appendix

Table 1: Demand Estimates

	Specifications for different values of λ							
	λ =0		λ =0.35		λ =0.70		λ =1	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Price Coefficient								
Constant	-1.221	0.129	-0.990	0.079	-0.656	0.043	-0.530	0.036
Income	0.023	0.005	0.024	0.005	0.023	0.005	0.023	0.005
Family Size	0.026	0.007	0.023	0.007	0.023	0.007	0.022	0.007
Income * Family Size	-0.003	0.001	-0.003	0.001	-0.003	0.001	-0.003	0.001
Search Cost								
Fixed Search Cost								
Constant	3.627	0.282	3.340	0.261	3.505	0.315	3.563	0.360
Income	0.043	0.045	0.057	0.043	0.046	0.045	0.041	0.047
Non-detergent Exp.	-0.014	0.001	-0.015	0.001	-0.014	0.001	-0.014	0.002
Marginal Search Cost								
Constant	3.341	0.296	4.048	0.421	3.719	0.514	3.653	0.617
Income	0.120	0.030	0.138	0.030	0.140	0.030	0.139	0.030
Display	-0.258	0.029	-0.183	0.026	-0.197	0.034	-0.202	0.041
Feature	-0.314	0.029	-0.222	0.028	-0.240	0.038	-0.247	0.047
Inventory	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Log-likelihood	-13,809		-13,806		-13,820		-13,829	
N	19,531		19,531		19,531		19,531	

Note: All specifications include brand-size fixed effects. For medium-size products the brand-size effects are interacted with a dummy for whether household income is above the median income, and therefore they will differ for these two groups. The simulation of inventory starts with an initial guess and then updates inventory in each week using the observed purchases and the estimated consumption. Asymptotic standard errors are reported. Specifications vary with respect to the value of λ

Table 2: Own-Price Elasticities

	λ =0	λ =0.35	λ =0.70	λ =1
TIDE Small	-2.495	-2.249	-1.959	-1.835
DYNAMO Small	-4.053	-3.122	-2.036	-1.626
PUREX Small	-2.754	-2.144	-1.414	-1.125
ARM Small	-3.045	-2.370	-1.529	-1.204
ALL Small	-2.890	-2.326	-1.750	-1.506
ERA Small	-3.508	-2.731	-1.780	-1.409
WISK Small	-5.694	-4.399	-2.960	-2.402
Private Small	-2.189	-1.727	-1.270	-1.082
Other Small	-3.015	-2.547	-1.957	-1.725
TIDE Medium	-2.364	-3.022	-2.975	-2.945
XTRA Medium	-0.850	-1.098	-1.128	-1.133
DYNAMO Medium	-2.920	-2.723	-2.318	-2.136
PUREX Medium	-1.373	-1.661	-1.637	-1.615
ARM Medium	-2.914	-2.466	-2.065	-1.883
ALL Medium	-2.251	-2.316	-2.179	-2.104
ERA Medium	-2.447	-2.441	-2.209	-2.094
WISK Medium	-3.628	-3.449	-2.914	-2.636
Private Medium	-2.089	-1.844	-1.572	-1.443
Other Medium	-1.880	-2.247	-2.154	-2.097
TIDE Large	-9.312	-8.425	-6.566	-5.839
XTRA Large	-4.504	-3.646	-2.703	-2.305
DYNAMO Large	-9.989	-7.746	-4.868	-3.762
PUREX Large	-7.908	-6.305	-4.485	-3.701
ARM Large	-8.715	-6.647	-4.415	-3.562
ALL Large	-11.483	-8.662	-5.589	-4.421
ERA Large	-10.594	-8.193	-5.617	-4.564
WISK Large	-17.343	-13.252	-8.197	-6.315
Private Large	-7.939	-6.091	-3.909	-3.085
Other Large	-11.811	-9.231	-5.928	-4.636

Note: Each cell reports the percent change in the market share of a product with a 1 percent change of its price. The results are based on the estimates in table 1.

Table 3: Marginal Costs

	λ =0	λ =0.35	λ =0.70	λ =1
TIDE Small	2.563	2.487	2.226	2.078
DYNAMO Small	2.966	2.652	2.022	1.549
PUREX Small	1.748	1.459	0.805	0.308
ARM Small	1.982	1.704	1.021	0.500
ALL Small	2.315	2.026	1.572	1.251
ERA Small	2.469	2.182	1.515	1.008
WISK Small	4.822	4.507	3.938	3.501
Private Small	1.361	1.041	0.545	0.203
Other Small	1.546	2.291	2.023	1.802
TIDE Medium	1.053	4.940	5.034	5.037
XTRA Medium	-0.792	0.221	0.313	0.331
DYNAMO Medium	1.856	3.109	2.959	2.817
PUREX Medium	-0.214	1.513	1.573	1.562
ARM Medium	2.668	2.659	2.394	2.203
ALL Medium	2.208	2.890	2.828	2.760
ERA Medium	2.179	2.958	2.878	2.780
WISK Medium	4.024	4.542	4.372	4.173
Private Medium	1.545	1.463	1.239	1.069
Other Medium	0.519	2.836	2.877	2.842
TIDE Large	4.707	13.040	12.913	12.716
XTRA Large	4.221	3.957	3.575	3.258
DYNAMO Large	8.522	8.226	7.565	7.006
PUREX Large	7.663	7.588	7.240	6.866
ARM Large	7.719	7.505	6.939	6.485
ALL Large	10.247	9.922	9.276	8.768
ERA Large	10.092	9.959	9.568	9.147
WISK Large	15.164	15.161	14.515	13.935
Private Large	6.760	6.462	5.762	5.236
Other Large	0.631	9.659	9.813	9.383

Note: Marginal costs are the mean over all the stores and weeks in our data. The results are based on the estimates in table 1.

Table 4: Product characteristics and effects on prices of a fall in search costs

	$\lambda = 0$			$\lambda = 0.35$			$\lambda = 0.70$			$\lambda = 1$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$	$\%\Delta Price$
Size	0.476		0.254	0.292		0.198	0.188		0.177*	0.0566		0.0859
	(1.324)		(0.733)	(0.534)		(0.264)	(0.112)		(0.0994)	(0.162)		(0.0709)
Share		-114.0***	-113.8***		-48.02***	-47.87***		-5.838***	-5.703***		14.97***	15.03***
		(14.19)	(14.44)		(5.157)	(5.203)		(2.034)	(1.958)		(1.408)	(1.397)
N	29	29	29	29	29	29	29	29	29	29	29	29
R^2	0.005	0.705	0.706	0.011	0.763	0.768	0.094	0.234	0.317	0.004	0.807	0.818

Note: The dependent variable in all regressions is the percentage change in prices when there is a fall in search costs equivalent to the mean (i.e., averaged over all households) fall created by displays and feature ads of all products. An observation is a product. Coefficients obtained from an OLS procedure. All specifications include a constant. Stars denote the significant level * p<0.10, ** p<0.05, *** p<0.01

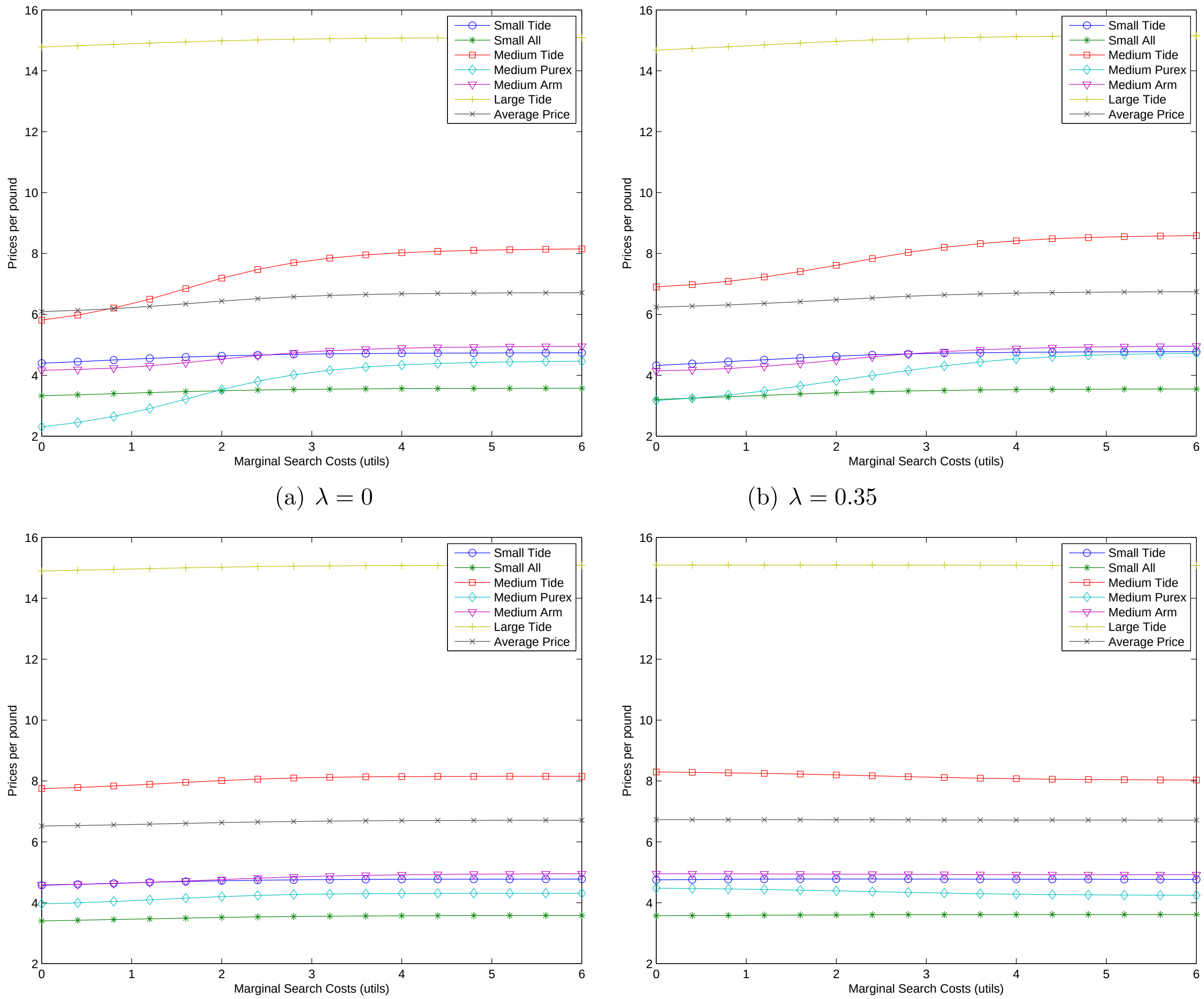
Table 5: Product characteristics and effects on profits of a fall in search costs

	$\lambda = 0$			$\lambda = 0.35$		
	(1)	(2)	(3)	(1)	(2)	(3)
	$\%\Delta Profit$	$\%\Delta Profit$	$\%\Delta Profit$	$\%\Delta Profit$	$\%\Delta Profit$	$\%\Delta Profit$
Size	5.105		8.254	0.246		0.751
	(17.02)		(6.568)	(3.191)		(1.987)
Share		1607.6***	1613.8***		258.2***	258.7***
		(130.6)	(129.3)		(38.49)	(39.14)
N	29	29	29	29	29	29
R^2	0.003	0.849	0.857	0.000	0.625	0.627

	$\lambda = 0.70$			$\lambda = 1$		
	(1)	(2)	(3)	(1)	(2)	(3)
	$\%\Delta Profit$	$\%\Delta Profit$	$\%\Delta Profit$	$\%\Delta Profit$	$\%\Delta Profit$	$\%\Delta Profit$
Size	3.570**		3.714***	4.546***		4.676***
	(1.395)		(1.219)	(1.275)		(1.120)
Share		70.90**	73.71***		62.86**	66.40***
		(27.42)	(24.00)		(27.95)	(22.05)
N	29	29	29	29	29	29
R^2	0.195	0.198	0.409	0.320	0.158	0.496

Note: The dependent variable in all regressions is the percentage change in profit when there is a fall in search costs equivalent to the mean fall created by displays and feature ads of all products. An observation is a product. Coefficients obtained from an OLS procedure. All specifications include a constant. Stars denote the significant level * p<0.10, ** p<0.05, *** p<0.01

Figure 1: Equilibrium prices (per pound) with respect to search costs



(a) $\lambda = 0$

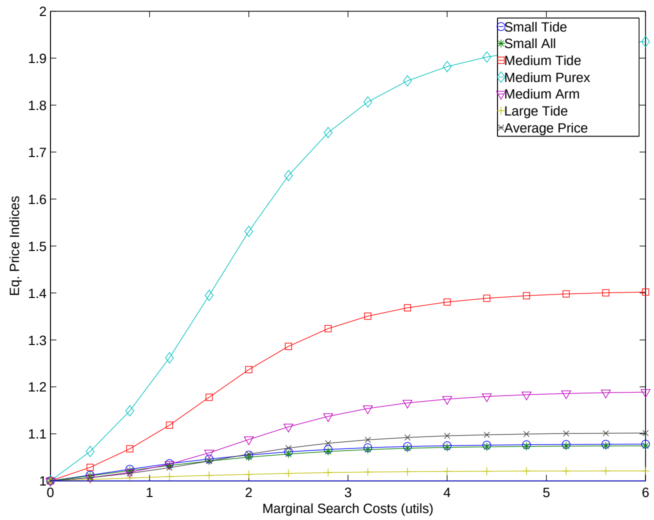
(b) $\lambda = 0.35$

(c) $\lambda = 0.70$

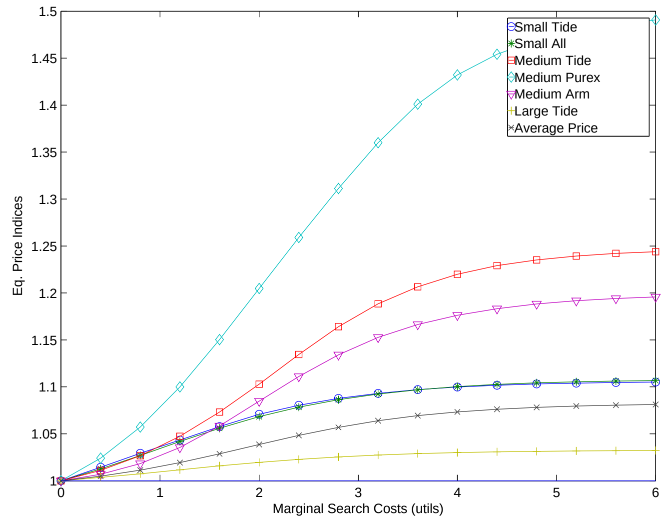
(d) $\lambda = 1$

Note: The search-cost value varies on the x-axis from 0 to 6 utils. The y-axis is the equilibrium price of a product. Equilibrium prices are the median for each product obtained from the equilibrium simulation using the demand estimates presented in table 1 and the recovered marginal costs. The simulation considers 50 draws (for each product) from the empirical distribution of marginal costs (excluding values below the 25th percentile and above the 75 percentile). Panel (a) considers $\lambda = 0$, panel (b) considers $\lambda = 0.35$, panel (c) considers $\lambda = 0.7$, and panel (d) considers $\lambda = 1$.

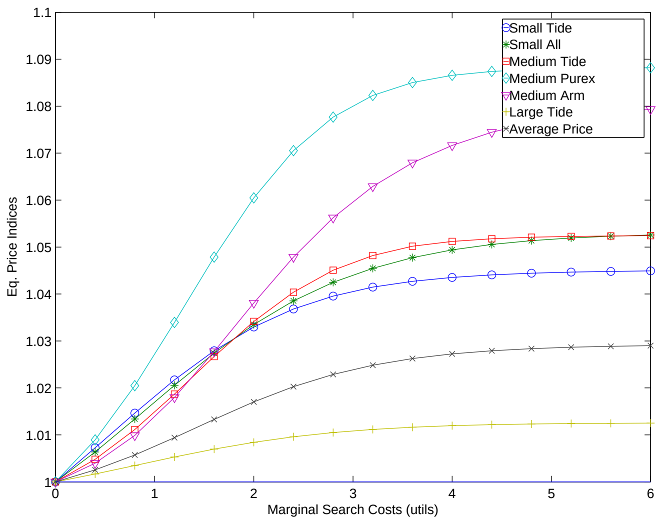
Figure 2: Equilibrium price indexes with respect to search costs



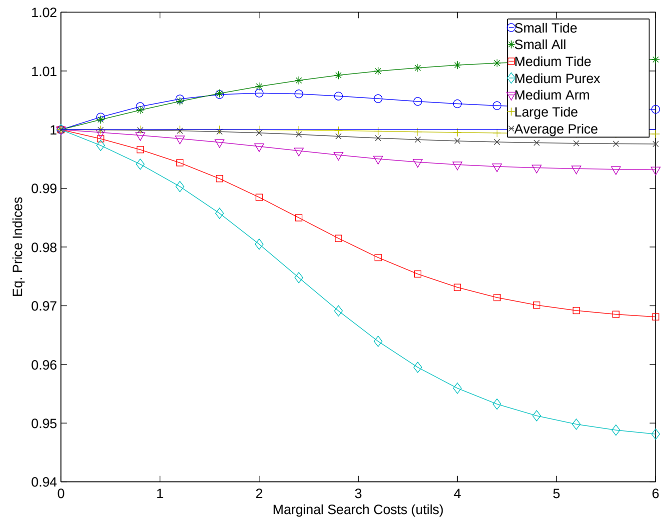
(a) $\lambda = 0$



(b) $\lambda = 0.35$



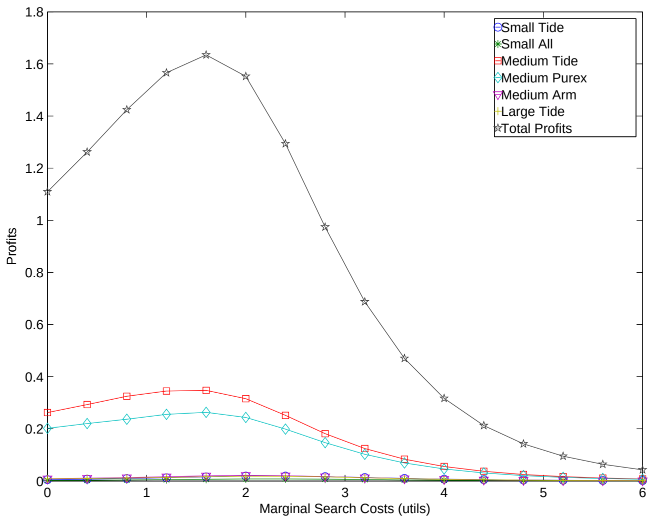
(c) $\lambda = 0.70$



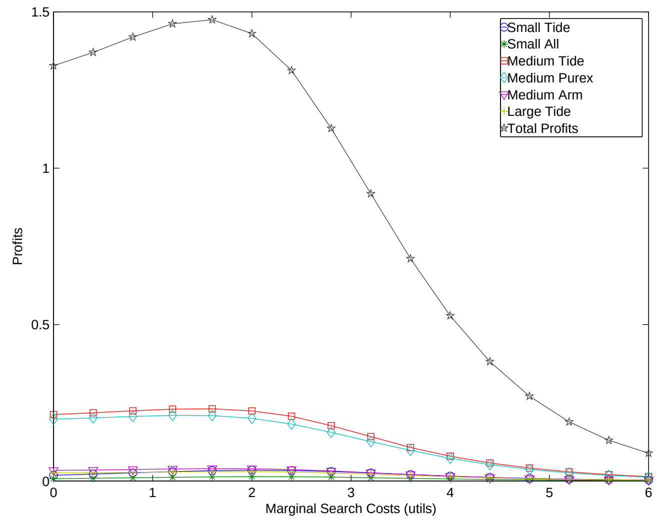
(d) $\lambda = 1$

Note: The equilibrium price index of a product at a specific value of search costs is the ratio of the equilibrium price of that product at that value of search costs to the equilibrium price of that product at a zero search cost. The equilibrium prices indexes are equal to 1 for a zero search cost. Indexes calculated using the equilibrium prices reported in figure 1. The search-cost value varies on the x-axis from 0 to 6 utils. Panel (a) considers $\lambda = 0$, panel (b) considers $\lambda = 0.35$, panel (c) considers $\lambda = 0.7$, and panel (d) considers $\lambda = 1$.

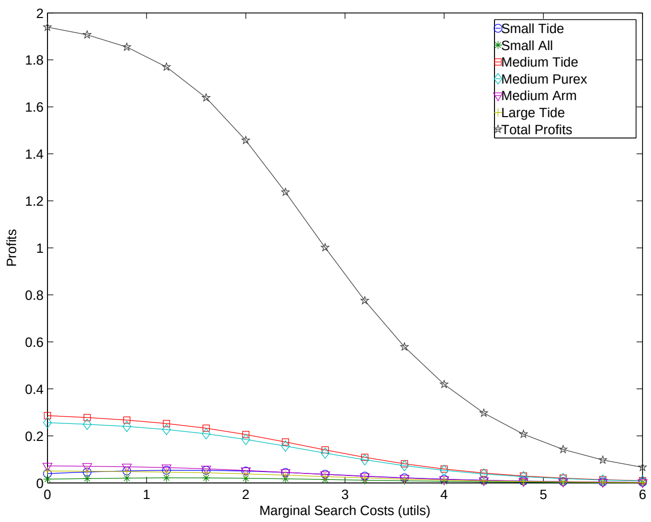
Figure 3: Equilibrium profits with respect to search costs



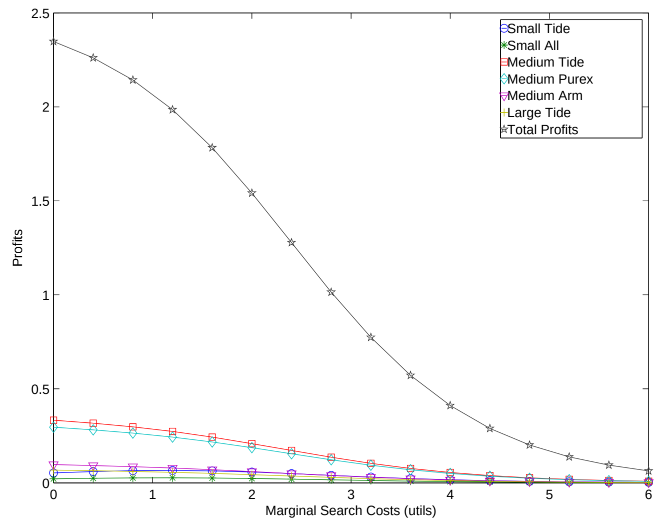
(a) $\lambda = 0$



(b) $\lambda = 0.35$



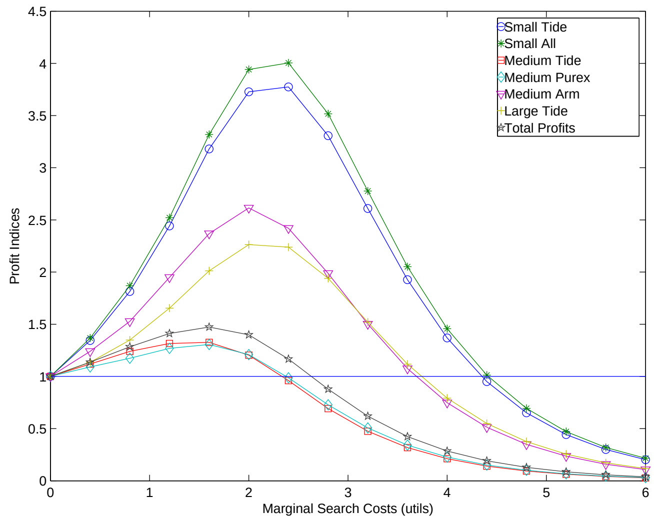
(c) $\lambda = 0.70$



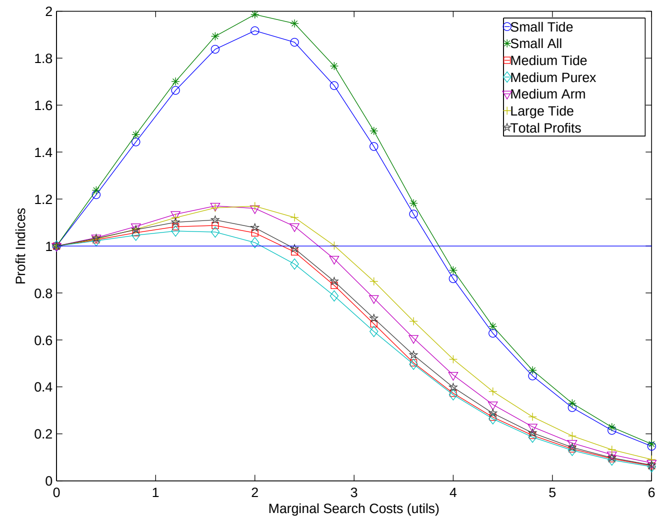
(d) $\lambda = 1$

Note: The search-costs value varies on the x-axis from 0 to 6 utils. Equilibrium profits are the median for each product obtained from the equilibrium simulation using the demand estimates presented in table 1 and the recovered marginal costs. Panel (a) considers $\lambda = 0$, panel (b) considers $\lambda = 0.35$, panel (c) considers $\lambda = 0.7$, and panel (d) considers $\lambda = 1$.

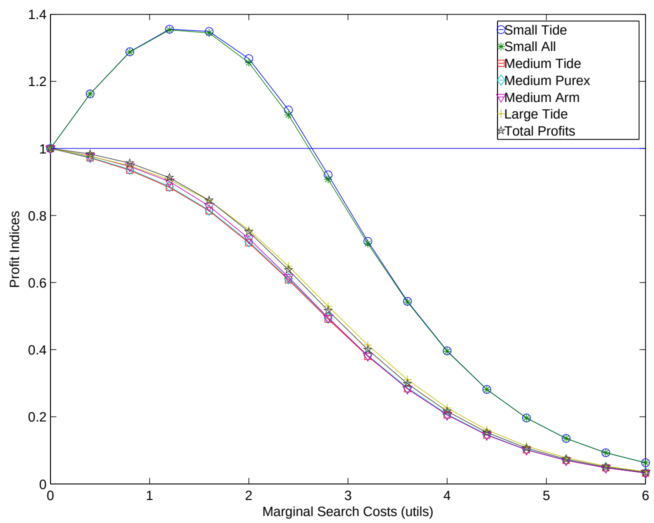
Figure 4: Equilibrium profit indexes with respect to search costs



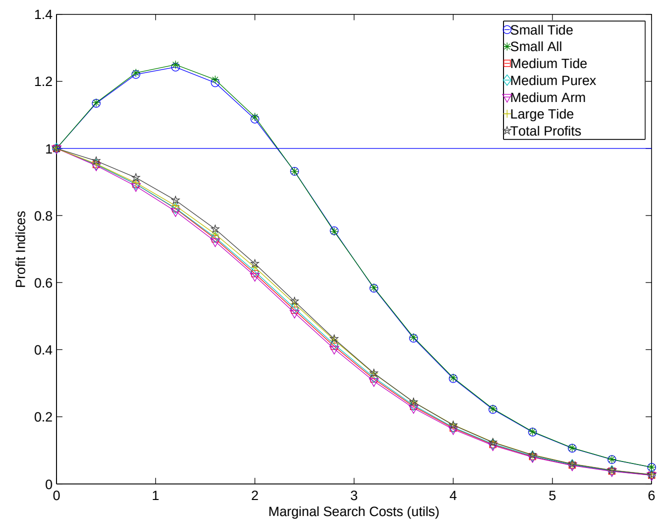
(a) $\lambda = 0$



(b) $\lambda = 0.35$



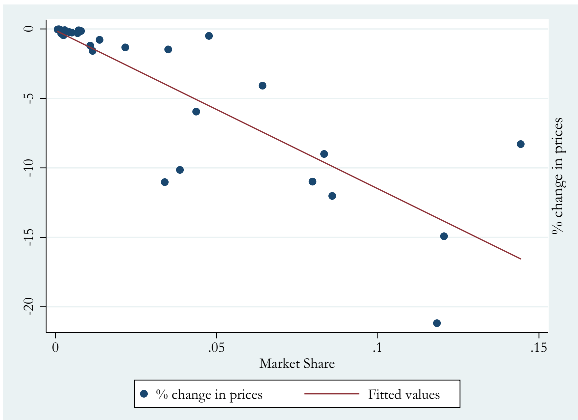
(c) $\lambda = 0.70$



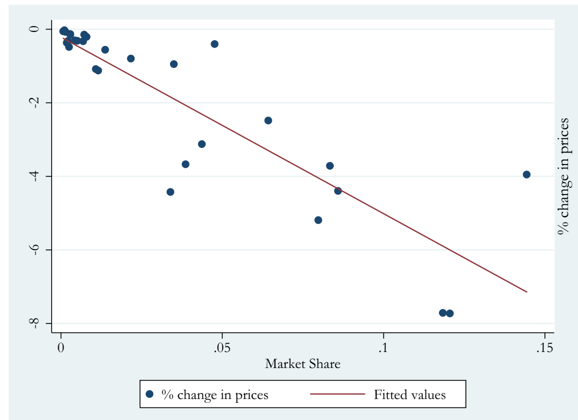
(d) $\lambda = 1$

Note: The equilibrium profit index of a product at a specific value of search costs is the ratio of the equilibrium profit of that product at that value of search costs to the equilibrium profit of that product at a zero search cost. Indexes calculated using the equilibrium profits reported in figure 3. The marginal-search-cost value varies on the x-axis from 0 to 6 utils. Panel (a) considers $\lambda = 0$, panel (b) considers $\lambda = 0.35$, panel (c) considers $\lambda = 0.7$, and panel (d) considers $\lambda = 1$.

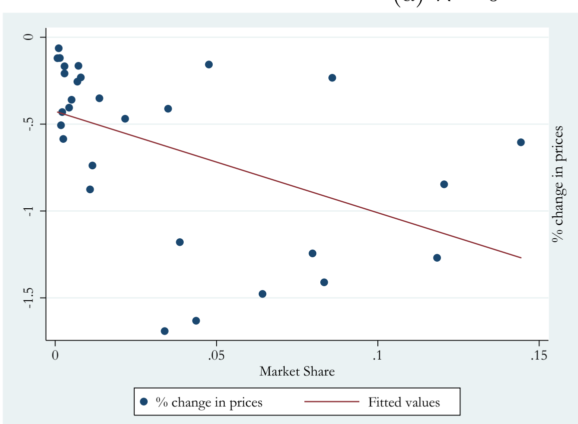
Figure 5: Effect on prices of display and feature ads with respect to product market share



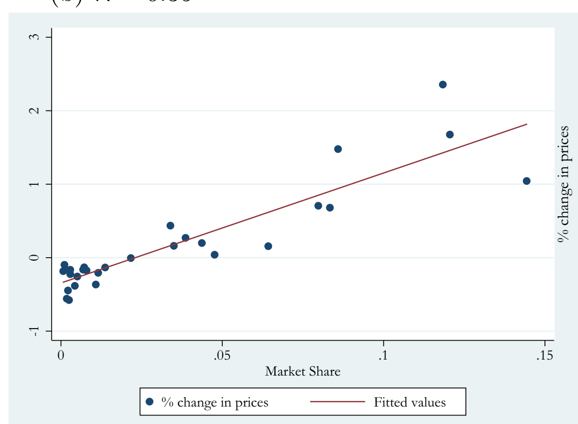
(a) $\lambda = 0$



(b) $\lambda = 0.35$



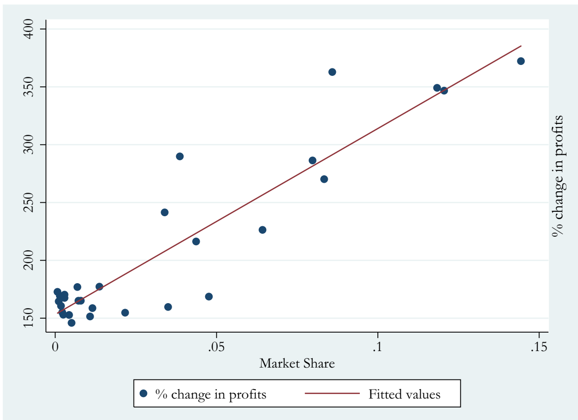
(c) $\lambda = 0.70$



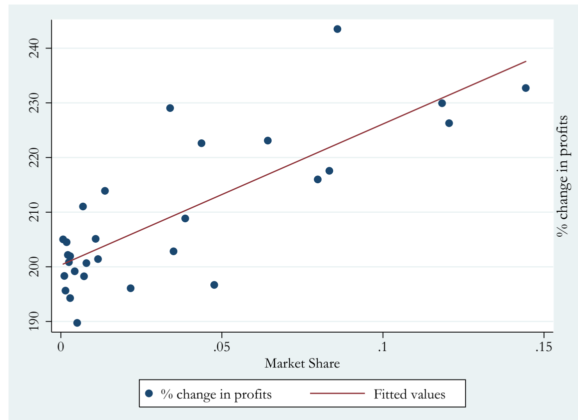
(d) $\lambda = 1$

Note: The figure reports the percentage change in the price of each product as a response to a fall in search costs equivalent to the mean (i.e., averaged over all households) fall created by displays and feature ads of all products. An observation is a product. The y-axis is the percentage change in the price of a product. The x-axis is the average market share of a product in the data. Panel (a) considers $\lambda = 0$, panel (b) considers $\lambda = 0.35$, panel (c) considers $\lambda = 0.7$, and panel (d) considers $\lambda = 1$.

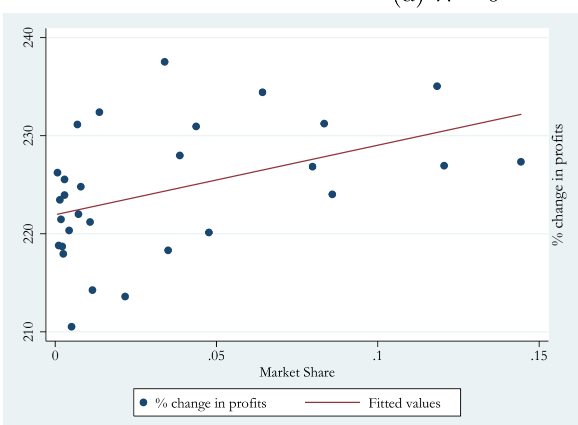
Figure 6: Effect on profits of display and feature ads with respect to product market share



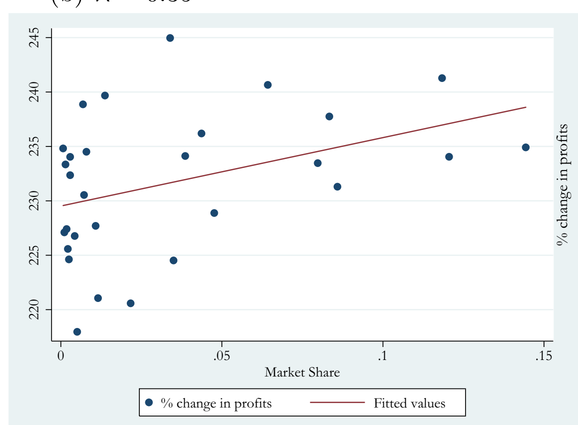
(a) $\lambda = 0$



(b) $\lambda = 0.35$



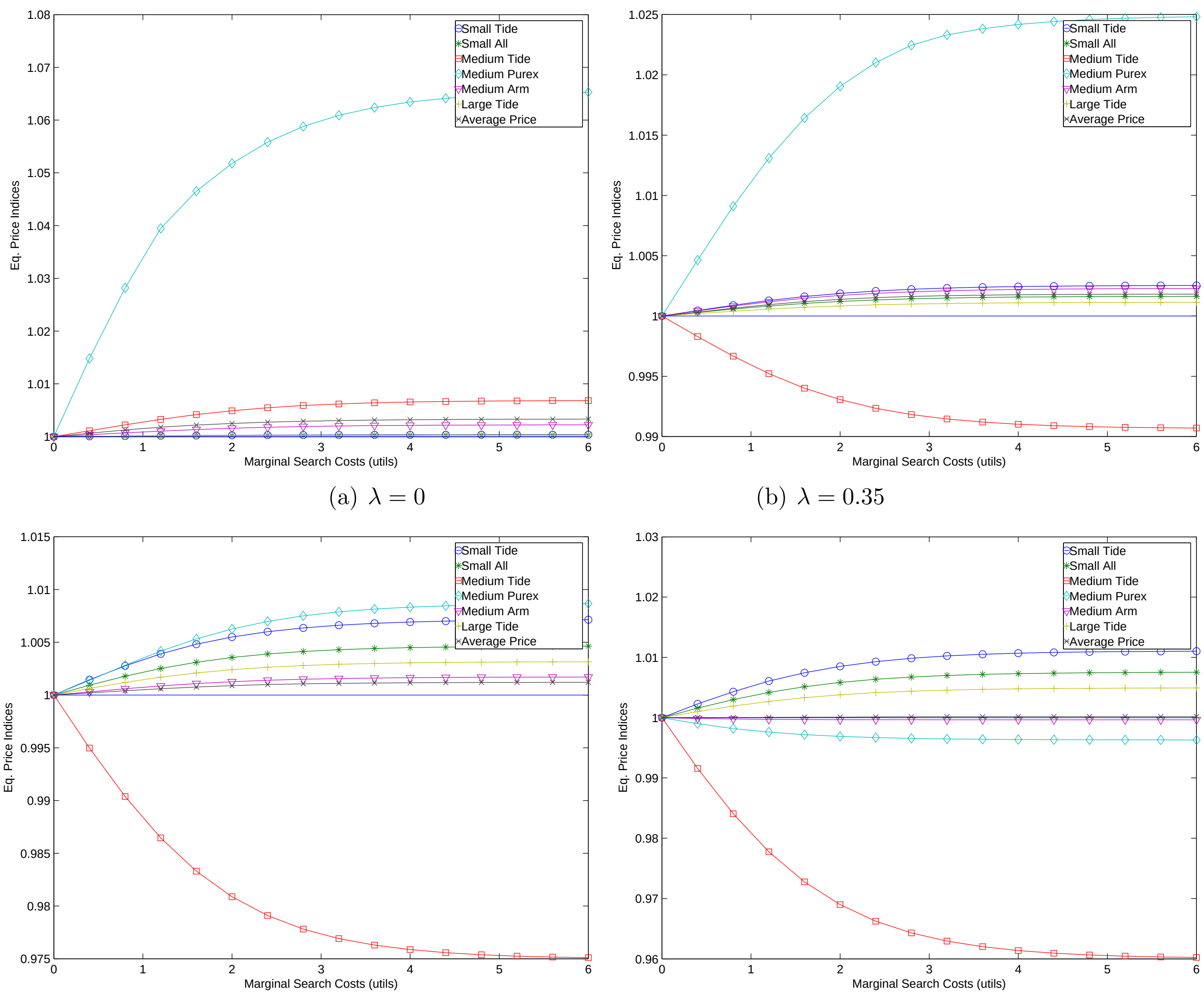
(c) $\lambda = 0.70$



(d) $\lambda = 1$

Note: The figure reports the percentage change in the profit of each product as a response to a fall in search costs equivalent to the mean fall created by displays and feature ads of all products. An observation is a product. The y-axis is the percentage change in the profit of a product. The x-axis is the average market share of a product in the data. Panel (a) considers $\lambda = 0$, panel (b) considers $\lambda = 0.35$, panel (c) considers $\lambda = 0.7$, and panel (d) considers $\lambda = 1$.

Figure 7: Equilibrium price indexes with respect to medium-package-Tide search costs



(a) $\lambda = 0$

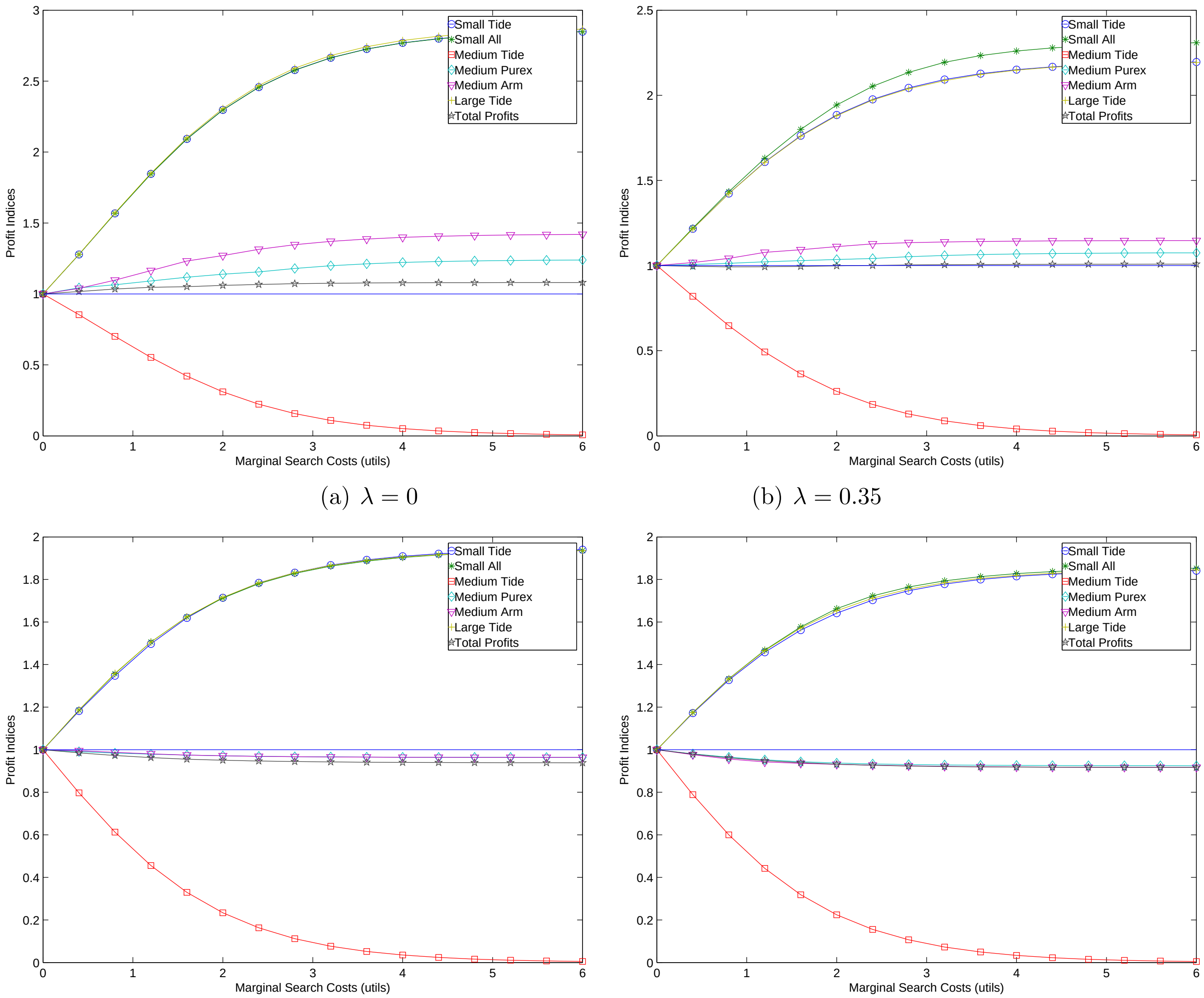
(b) $\lambda = 0.35$

(c) $\lambda = 0.70$

(d) $\lambda = 1$

Note: The equilibrium prices indexes are equal to 1 for a zero search cost. The medium-package-Tide search-cost value varies on the x-axis from 0 to 6 utils. Panel (a) considers $\lambda = 0$, panel (b) considers $\lambda = 0.25$, panel (c) considers $\lambda = 0.5$, panel (d) considers $\lambda = 0.75$, and panel (e) considers $\lambda = 1$.

Figure 8: Equilibrium profit indexes with respect to medium-package-Tide search costs



(a) $\lambda = 0$

(b) $\lambda = 0.35$

(c) $\lambda = 0.70$

(d) $\lambda = 1$

Note: The equilibrium profit indexes are equal to 1 for a zero search cost. The medium-package-Tide marginal-search-cost value varies on the x-axis from 0 to 6 utils. Panel (a) considers $\lambda = 0$, panel (b) considers $\lambda = 0.25$, panel (c) considers $\lambda = 0.5$, panel (d) considers $\lambda = 0.75$, and panel (e) considers $\lambda = 1$.